In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import scipy.stats as spstats
import sklearn
import seaborn as sns
import datetime

# brewery_id,brewery_name,review_time,review_overall,
# review_aroma,review_appearance,review_profilename,
# beer_style,review_palate,review_taste,beer_name,beer_abv,beer_beerid

def timestamp_to_datetime(ts):
    """
    Convert a timestamp to a datetime.
    ts: epoch in seconds since 1970-01-01
    """
    return datetime.datetime.fromtimestamp(float(ts))

main_df = pd.read_csv(
    'beer_reviews.csv',
    parse_dates=['review_time'],
    date_parser=timestamp_to_datetime
)

main_df.head()
```

Out[1]:

	brewery_id	brewery_name	review_time	review_overall	review_aroma	review_appearance	review_profilenan
0	10325	Vecchio Birraio	2009-02-16 12:57:03	1.5	2.0	2.5	stcul
1	10325	Vecchio Birraio	2009-03-01 05:44:57	3.0	2.5	3.0	stcul
2	10325	Vecchio Birraio	2009-03-01 06:10:04	3.0	2.5	3.0	stcul
3	10325	Vecchio Birraio	2009-02-15 11:12:25	3.0	3.0	3.5	stcul
4	1075	Caldera Brewing Company	2010-12-30 10:53:26	4.0	4.5	4.0	johnmichaels

1. Prep work and EDA

Data cleaning procedures

- ABV: replace negative with 0
- review scores: clip within [1,5]

For `beer_df` (1 row for each beer):

- all procedures above
- ABV, style, name, brewery id: use the mode (most frequent value) for this beer's id

In [2]:
```
def cleanup(df):
    df.rename(
        {
            'beer_beerid':'bid',
            'beer_abv':'abv',
            'beer_style':'style',
            'beer_name': 'name',
            'review_profilename':'reviewer',
        },
        axis='columns',
        inplace=True
    )
    df.dropna(inplace=True) # dropping is quick and dirty, could be smarter, eg rep
lace with avg or -1

    # keep review scores within 1-5 range
    # https://www.beeradvocate.com/community/threads/how-to-review-a-beer.241156/
    review_columns = [
        'review_aroma',
        'review_appearance',
        'review_palate',
        'review_taste',
        'review_overall'
    ]
    df[review_columns] = df[review_columns].clip(1, 5)
    df['abv'].clip(lower=0, inplace=True)
    df['style'] = df['style'].astype('category') # TODO: df['style_cat'] = df['styl
e'].cat.codes
    # df.set_index('bid',inplace=True) # TODO: make this idempotent
    return df

main_df = cleanup(main_df)
main_df.sample(3,random_state=123)
```

Out[2]:

	brewery_id	brewery_name	review_time	review_overall	review_aroma	review_appearance	reviewer
1237288	604	Brasserie Dubuisson Frères sprl	2010-03-18 18:24:54	4.0	4.5	4.0	NHGrafx
699067	130	Boulder Beer / Wilderness Pub	2008-08-30 10:19:19	4.0	4.5	3.5	DHermit
1551529	345	Victory Brewing Company	2007-05-10 02:21:14	5.0	4.5	4.0	Beertron

In [3]:
```
main_df.describe()
```

Out[3]:

	brewery_id	review_overall	review_aroma	review_appearance	review_palate	review_taste	a
count	1.518478e+06	1.518478e+06	1.518478e+06	1.518478e+06	1.518478e+06	1.518478e+06	1.518478e+
mean	3.074306e+03	3.823942e+00	3.746218e+00	3.850388e+00	3.753735e+00	3.804082e+00	7.042488e+
std	5.544339e+03	7.172449e-01	6.953440e-01	6.142854e-01	6.793350e-01	7.286079e-01	2.322568e+
min	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e
25%	1.410000e+02	3.500000e+00	3.500000e+00	3.500000e+00	3.500000e+00	3.500000e+00	5.200000e+
50%	4.170000e+02	4.000000e+00	4.000000e+00	4.000000e+00	4.000000e+00	4.000000e+00	6.500000e+
75%	2.298000e+03	4.500000e+00	4.000000e+00	4.000000e+00	4.000000e+00	4.500000e+00	8.500000e+
max	2.800300e+04	5.000000e+00	5.000000e+00	5.000000e+00	5.000000e+00	5.000000e+00	5.770000e+

In [4]:
```
# Build a beer dataset, ie one row per beer.
def mode(series):
    """ given a series, return its mode
    https://github.com/pandas-dev/pandas/issues/11562
    """
    return pd.Series.mode(series)[0]

def build_beer_df(df):
    beer_df = ( # one row per beer
        df
        .groupby('bid')
        .agg({
            'brewery_id':mode, # get most frequently-given brewery, in case of DQ i
ssue
            'style':mode,
            'name':mode,
            'abv':mode,
            'review_overall':['count','mean','std'], # TODO: compute pct reviews gi
ving N stars
            'review_aroma':['mean','std'],
            'review_appearance':['mean','std'],
            'review_palate':['mean','std'],
            'review_taste':['mean','std'],
        })
    )
    beer_df.columns = ["_".join(x) for x in beer_df.columns.ravel()] # flatten mult
i-index
    beer_df.rename(
        {
            'brewery_id_mode': 'brewery_id',
            'review_overall_count': 'n_reviews',
            'abv_mode': 'abv',
            'style_mode':'style',
            'name_mode':'name'
        },
        axis='columns',
        inplace=True
    )
    return beer_df

beer_df = build_beer_df(main_df)
beer_df.head()
```

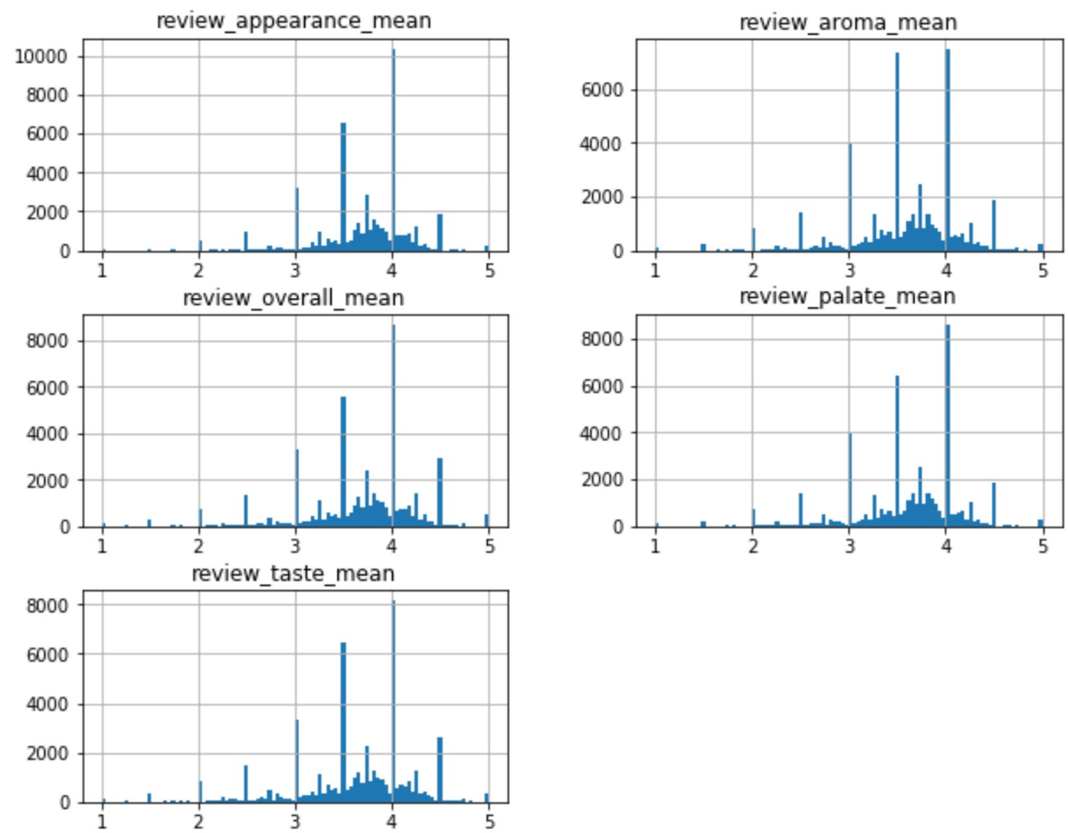
Out[4]:

	brewery_id	style	name	abv	n_reviews	review_overall_mean	review_overall_std	review_aroma_n
bid								
5	3	Vienna Lager	Amber	4.5	424	3.549528	0.676278	3.20
6	3	English Brown Ale	Turbodog	5.6	877	3.706956	0.629096	3.51
7	3	Fruit / Vegetable Beer	Purple Haze	4.2	659	3.266313	0.823304	3.17
8	3	American Adjunct Lager	Wheat	4.2	68	3.647059	0.872716	3.08
9	3	American Pale Lager	Golden	4.2	116	3.400862	0.746644	2.85

In [ ]:

In [5]:

```
# what are the ratings like?
def histogram_avg_review_scores(df):
    review_mean_columns = [
        'review_aroma_mean',
        'review_appearance_mean',
        'review_palate_mean',
        'review_taste_mean',
        'review_overall_mean'
    ]
    df[review_mean_columns].hist(bins=100,figsize=(10,8))
    # beer_df[review_mean_columns].plot.kde()

histogram_avg_review_scores(beer_df)
```



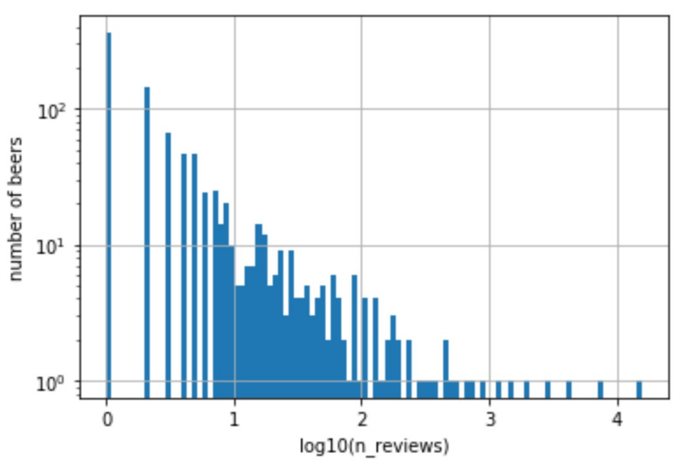
2. Weirdest beers

Weird is a vague term. Let's look at beers that stand out in some way. Take-aways of this section:

- `90 Minute IPA` is the most reviewed beer (3289 reviews), when 30% of beers have only 1 review.
- `Genesee NA` has the lowest ABV: .05%. FYI this is the legal threshold for alcohol-free [in the UK (https://en.wikipedia.org/wiki/Low-alcohol_beer)](https://en.wikipedia.org/wiki/Low-alcohol_beer).
- `Sink The Bismarck!` has the highest ABV, 41%. Similar ABV as Whisky.
- 100 reviews is a good threshold for "popular" beers: beers with 100+ reviews make up 6% of beers and 74% of reviews. For reference, the typical rating for popular beers is 3.7.
- `Crazy Ed's Cave Creek Chili Beer` has the lowest rating of popular beers at 1.49. Why are so many people drinking it? Is it so bad that it's actually good?
- `Citra DIPA` has the highest rating of popular beers at 4.63. This is a lot. >99% of popular beers are below 4.5.

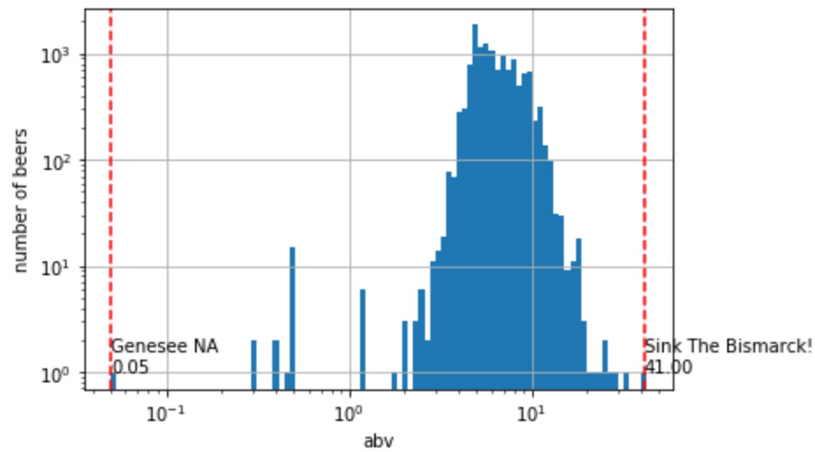
In [6]:
```
# are there very popular beers that get reviewed a lot? how many are reviewed only
once?
def eda_histogram_popularity(beer_df):
    fig, ax = plt.subplots()
    np.log10(beer_df['n_reviews'].value_counts()).hist(bins=100)
    ax.set(xlabel="log10(n_reviews)", ylabel="number of beers", yscale='log')
    print(f"total beers: {len(beer_df)}")
    print(f"beers with >1k reviews: {len(beer_df.query('n_reviews>1000'))} ")
    print(f"beers with 1 review: {len(beer_df.query('n_reviews==1'))} ")
    print(f"beers with 10+ reviews: {len(beer_df.query('n_reviews>=10'))} ")
    name, reviews = beer_df.loc[beer_df['n_reviews'].idxmax(),['name','n_reviews']]
    pct_reviews = reviews / beer_df['n_reviews'].sum()*100
    print(f"beer with most reviews: `{name}` has {reviews} reviews, which is {pct_r
eviews:.2f}% of all reviews")

eda_histogram_popularity(beer_df)
```

```
total beers: 49000
beers with >1k reviews: 199
beers with 1 review: 15617
beers with 10+ reviews: 12878
beer with most reviews: `90 Minute IPA` has 3289 reviews, which is 0.22% of all
reviews
```



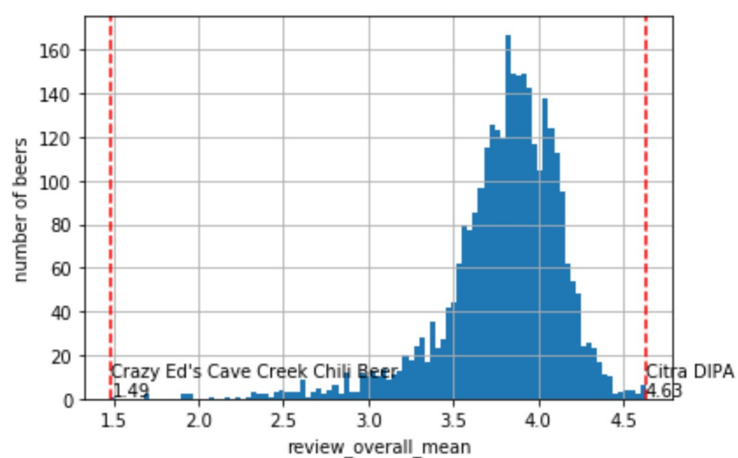
In [7]:
```
# Looks like lots of beers have only 1 review.
# The beer might be obscure, or the review unreliable, or user typos in beer name g
enerate new ids.

# Let's look at ABV: keep only beers with 10+ reviews and abv>0.

def build_popular_beer_df(beer_df,n_reviews=100):
    """ given df with one row per beer, keep only beers with at least n_reviews and
abv>0 """
    return beer_df.query(f"n_reviews>={n_reviews} & abv>0")

def eda_abv(beer_df):
    """ return nothing """
    n_zero_abv_beers = len(beer_df.query('abv==0'))
    print(f"number of beers with zero abv: {n_zero_abv_beers}")

# weird beers: min and max abv
def plot_hist_and_print_min_max(df, value_column, name_column, ylabel, loglog=Fals
e, nbins=100):
    """ Plot a histogram of value_column for this df.
    Indicate the name of min and max on plot, using df[name_column].
    return nothing
    """
    min_name, min_val = df.loc[df[value_column].idxmin(),[name_column,value_colum
n]]
    max_name, max_val = df.loc[df[value_column].idxmax(),[name_column,value_colum
n]]

    if loglog:
        bins = np.logspace(np.log10(min_val), np.log10(max_val+1), nbins)
    else:
        bins = np.linspace(min_val, max_val, nbins)

    ax = df[value_column].hist(bins=bins)
    scale = 'log' if loglog else 'linear'
    ax.set(xlabel=value_column, ylabel=ylabel, yscale=scale, xscale=scale)

    ax.axvline(min_val, color='r', linestyle='--')
    ax.text(min_val,1,f"{min_name}\n{min_val:.2f}")

    ax.axvline(max_val, color='r', linestyle='--')
    ax.text(max_val,1,f"{max_name}\n{max_val:.2f}")


eda_abv(beer_df)
bdf = build_popular_beer_df(beer_df, n_reviews=10)
plot_hist_and_print_min_max(bdf, 'abv', 'name', 'number of beers', loglog=True)
```

```
number of beers with zero abv: 0
```



In [8]:
```
# beer (with at least 100 reviews) with highest review score
def eda_nreviews(bdf):
    """ EDA. bdf is df indexed on beer. return nothing """
    n_beers = len(bdf)
    pct_beers = 100*len(bdf) / len(beer_df)
    pct_reviews = 100 * bdf['n_reviews'].sum() / beer_df['n_reviews'].sum()
    print(f"{n_beers} beers have 100+ reviews ({pct_beers :.2f}% of all beers, {pct
_reviews:.2f}% of reviews)")

bdf = build_popular_beer_df(beer_df, n_reviews=100)
eda_nreviews(bdf)
plot_hist_and_print_min_max(bdf, 'review_overall_mean', 'name', 'number of beers')
```

```
3083 beers have 100+ reviews (6.29% of all beers, 73.51% of reviews)
```



3. What drives the overall review score?

Summary:

- Top factors: `average taste score` predicts overall score the most. Second is `average palate score` , third `ABV` .
- Quantifying their importance is difficult. Reviewers provide very similar scores for overall, taste, palate, etc. This makes it difficult to get a separate signal for taste and palate.
- On the plus side, the top 3 factors are sufficient to explain >90% of variance in the overall score.
- Methods: we tried 2 random forest methods to quantify feature importance: 1) feature variance/MSE, and 2) relative impact of dropping feature on R2.

In [9]:

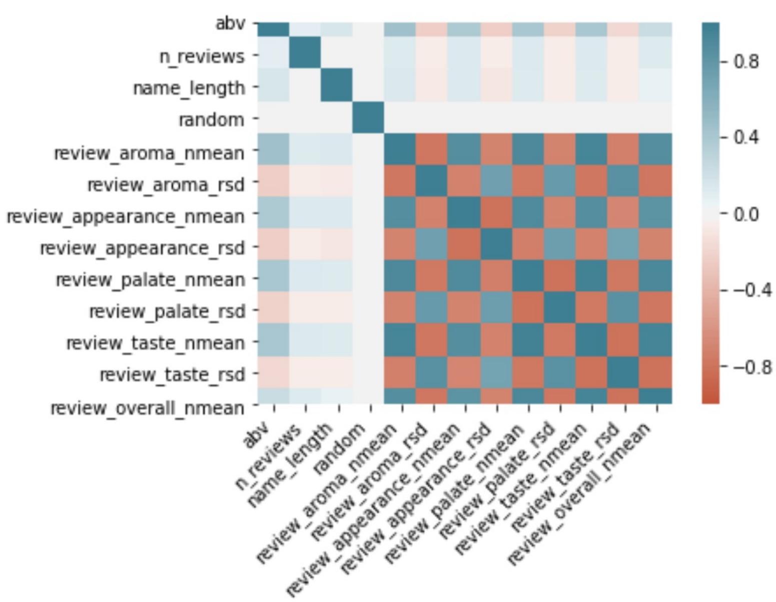
```
def build_review_score_drivers_df(beer_df, min_reviews=10):
    """ takes a df with one row per beer
    add some columns, normalize some, drop others
    return a df with one row per beer
    """
    bdf = beer_df.query(f"n_reviews>={min_reviews}").copy() # keep only beers with enough reviews

    # add some features that may be useful
    bdf['random'] = np.random.random(size = len(bdf)) # add random for baseline importance
    bdf['name_length'] = bdf['name'].str.len() # theory: longer names sound fancier and bias ratings upward

    # compute relative sd, aka CV https://en.wikipedia.org/wiki/Coefficient_of_variation
    review_props = ['aroma','appearance','palate','taste','overall']
    for prop in review_props:
        bdf[f'review_{prop}_rsd'] = bdf[f'review_{prop}_std'] / bdf[f'review_{prop}_mean']

    # normalize means
    for prop in review_props:
        colname = f'review_{prop}_mean'
        bdf[f'review_{prop}_nmean'] = (bdf[colname] - bdf[colname].mean()) / bdf[colname].std()

    # TODO: categorize style, eg boolean for Lager vs Ale

    # keep only usable features
    features_colnames = [
        'abv',
        'n_reviews',
        'name_length',
        'random',
        'review_aroma_nmean',
        'review_aroma_rsd',
        'review_appearance_nmean',
        'review_appearance_rsd',
        'review_palate_nmean',
        'review_palate_rsd',
        'review_taste_nmean',
        'review_taste_rsd',
    ]
    label_colname = 'review_overall_nmean'
    bdf = bdf[features_colnames + [label_colname]]
    return bdf

bdf = build_review_score_drivers_df(beer_df)
print(f'bdf shape: {bdf.shape}')
bdf.sample(5,random_state=456)
```

```
bdf shape: (12878, 13)
```

Out[9]:

	abv	n_reviews	name_length	random	review_aroma_nmean	review_aroma_rsd	review_appearance_n
bid							
4528	5.90	48	22	0.577428	-0.039046	0.131931	0.09
3747	5.20	58	15	0.471369	-0.275918	0.168340	-0.42
1163	5.20	837	21	0.707501	-0.042000	0.144418	0.69
22919	4.75	81	12	0.590291	-0.150990	0.121378	0.35
64091	5.50	15	13	0.389449	0.199090	0.150732	-0.25

In [10]:
```
# this is too slow

# from scipy.stats import pearsonr

# def corrfunc(x, y, ax=None, **kws):
#     """Plot the correlation coefficient in the top left hand corner of a plot.
#     https://stackoverflow.com/a/50835066
#     """
#     r, pval = pearsonr(x, y)
#     ax = ax or plt.gca()
#     ax.annotate(f'r = {r:.2f}', xy=(.1, .9), xycoords=ax.transAxes)

# review_columns = [f'review_{s}_nmean' for s in review_props]
# g = sns.pairplot(
#     bdf,
#     kind="reg",
#     markers='+',
#     plot_kws={'line_kws':{'color':'red'}}
# )
# g.map_lower(corrfunc) # add pearson r
# plt.show()

# this is faster, and all we really need
# https://towardsdatascience.com/better-heatmaps-and-correlation-matrix-plots-in-py
thon-41445d0f2bec
def plot_correl_matrix(bdf):
    corr = bdf.corr()
    ax = sns.heatmap(
        corr,
        vmin=-1, vmax=1, center=0,
        cmap=sns.diverging_palette(20, 220, n=200),
        square=True
    )
    ax.set_xticklabels(
        ax.get_xticklabels(),
        rotation=45,
        horizontalalignment='right'
    )

plot_correl_matrix(bdf)
```



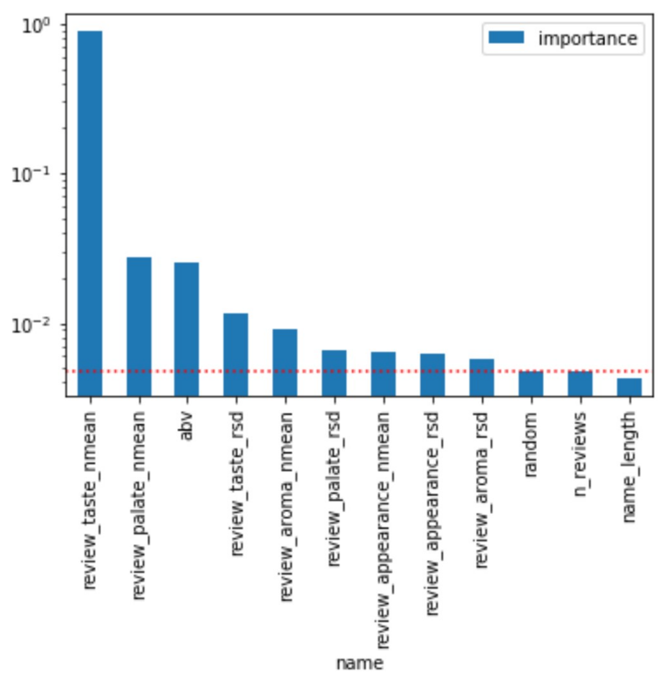
Some take-aways from the correlation matrix above:

1. The average scores for aroma, appearance, palate, and taste, are all correlated with each other, and with the overal score. There are 2 possible explanations: The first, is that reviewers don't make the difference between the 5 scores, so we should probably change the prompts or educate reviewers about them. Another possibility is that beers are good-all-around or bad-all-around, ie a good aroma always comes together with a good palate and taste (which is believable) and appearance (less believable). Either way, we need to tackle this colinearity issue. One solution would be to reduce the 4 dimensions into 1-2, eg via PCA, but this would lose some interpretability. Another solution is to keep only one of those features, but then we lose their contribution, which could be big *after* random forest picked the first feature (eg aroma). Quick and dirty non-solution: keep all features and remember the colinearity.
2. For all 4 review factors, RSDs are always strongly negatively correlated with the factor means and with the overall mean. This means when beers have a high overall score, reviews are typically in agreement. When beers have a lower overall score, reviews are more spread out.
3. All 4 RSDs are super negatively correlated with overall score. Let's keep only `review_taste_rsd`.
4. Higher ABV, longer names, and higher popularity (more reviews) correlate with higher overall score.

In [11]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split


def prep_train_valid_sets(df, label, column_blacklist=[], seed=123):
    """
    Return train and validation sets
    Plot feature importance in barplot
    """
    # ignore columns in blacklist
    features = [col for col in bdf.columns if col != label and col not in column_bl
acklist]

    # split
    x_train, x_valid, y_train, y_valid = train_test_split(
        df[features],
        df[label],
        test_size = 0.8,
        random_state = seed
    )
    return x_train, x_valid, y_train, y_valid


def train_rf(x_train, y_train, n_trees=200, seed=123):
    """ Return a random forest regressor of y ~ x """
    rf = RandomForestRegressor(
        n_estimators = n_trees,
        n_jobs = -1,
        oob_score = True,
        bootstrap = True,
        random_state = seed
    )
    rf.fit(x_train, y_train)
    return rf


def compute_rf_perf_and_importance(rf, x_train, y_train, x_valid, y_valid):
    """
    Given a random forest model, compute R2 and feature importances.
    Return:
    - model performance: r-square on train, on OOB during training, and on validati
on.
    - df mapping each feature name to its importance in [0,1]
    """
    # https://towardsdatascience.com/explaining-feature-importance-by-example-of-a-
random-forest-d9166011959e
    # https://scikit-learn.org/stable/auto_examples/ensemble/plot_forest_importance
s.html

    # performance scores
    r2_train = rf.score(x_train, y_train)
    r2_oob = rf.oob_score_
    r2_valid = rf.score(x_valid, y_valid)

    # feature importance
    importance_df = (
        pd.DataFrame({
            'name': list(x_train.columns),
            'importance': rf.feature_importances_
        })
        .set_index('name')
        .sort_values('importance', ascending=False)
    )
```

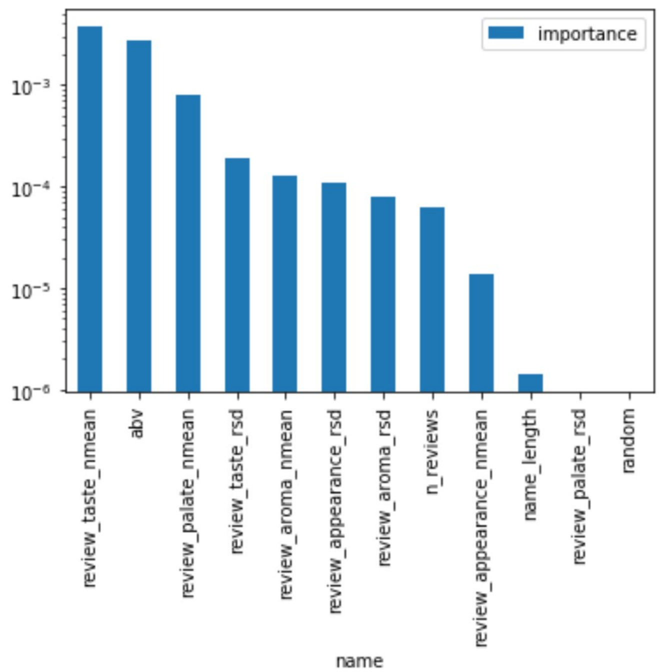
In [12]:
```
# let's finally get and plot importances
def get_factor_importance(bdf, label, column_blacklist=[]):
    """ Wrap all functions above together.
    given a beer df and continuous label, train a regression forest,
    print its performance, return nothing.
    """
    x_train, x_valid, y_train, y_valid = prep_train_valid_sets(bdf, label)
    rf = train_rf(x_train, y_train)
    r2_train, r2_oob, r2_valid, importance_df = compute_rf_perf_and_importance(rf,
x_train, y_train, x_valid, y_valid)
    display_perf_importance(r2_train, r2_oob, r2_valid, importance_df)

get_factor_importance(bdf, 'review_overall_nmean')
```

```
r2 train: 0.99
r2 oob: 0.92
r2 valid: 0.93
                          importance
name
review_taste_nmean          0.887774
review_palate_nmean         0.027431
abv                         0.025287
review_taste_rsd            0.011587
review_aroma_nmean          0.009121
review_palate_rsd           0.006663
review_appearance_nmean     0.006366
review_appearance_rsd       0.006228
review_aroma_rsd            0.005736
random                      0.004783
n_reviews                   0.004740
name_length                 0.004285
```



In [13]:
```
# try another approach to measure importance: impact on R2 of dropping a feature
# https://towardsdatascience.com/explaining-feature-importance-by-example-of-a-rand
om-forest-d9166011959e
from sklearn.base import clone

def compute_rf_perf_ft_imp_dropping(rf, x_train, y_train, x_valid, y_valid):
    """
    Given a random forest model, compute R2 and feature importances.
    In this case, feature importance means impact on R2 of dropping the feature.
    Return:
    - model performance: r-square on train, on OOB during training, and on validati
on.
    - df mapping each feature name to its importance in [0,1]
    """

    # performance scores
    r2_train = rf.score(x_train, y_train)
    r2_oob = rf.oob_score_
    r2_valid = rf.score(x_valid, y_valid)

    # clone model, removing each feature, one at a time, storing importance
    importances = []
    for col in x_train.columns:
        rf_clone = clone(rf) # also copies seed, n_trees, ... everything in rf.get_
params() !
        rf_clone.fit(x_train.drop(col, axis = 1), y_train)
        r2_train_clone = rf_clone.score(x_train.drop(col, axis = 1), y_train)
        importances.append(r2_train - r2_train_clone)

    # feature importance
    importance_df = (
        pd.DataFrame({
            'name': list(x_train.columns),
            'importance': importances #rf.feature_importances_
        })
        .set_index('name')
        .sort_values('importance', ascending=False)
    )

    return r2_train, r2_oob, r2_valid, importance_df


# let's finally get and plot importances
def get_factor_importance_dropping(bdf, label, column_blacklist=[]):
    """ Wrap all functions above together.
    given a beer df and continuous label, train a regression forest,
    print its performance, return nothing.
    """
    x_train, x_valid, y_train, y_valid = prep_train_valid_sets(bdf, label)
    rf = train_rf(x_train, y_train)
    r2_train, r2_oob, r2_valid, importance_df = compute_rf_perf_ft_imp_dropping(rf,
x_train, y_train, x_valid, y_valid)
    display_perf_importance(r2_train, r2_oob, r2_valid, importance_df)


get_factor_importance_dropping(bdf, 'review_overall_nmean')
```

```
r2 train: 0.99
r2 oob: 0.92
r2 valid: 0.93
                         importance
name
review_taste_nmean         0.003724
abv                        0.002692
review_palate_nmean        0.000800
review_taste_rsd           0.000187
review_aroma_nmean         0.000126
review_appearance_rsd      0.000108
review_aroma_rsd           0.000080
n_reviews                  0.000061
review_appearance_nmean    0.000014
name_length                0.000001
review_palate_rsd         -0.000041
random                    -0.000069
```



Take-aways:

- Average taste and palate scores remain important, as well as ABV
- Colinearity is so big that the impact on R2 of removing a feature (ie the plot's y axis) is super small.

3. Reviewers most likely paid by beer companies

This section explores 2 definitions for "being paid":

1. Reviewing many beers from a given brewery: user `feloniousmonk` for brewery `Minneapolis Town Hall Brewery`.
2. Giving a score abnormally high to many beers from this brewery: `MrHurmateeowish` for brewery `Anheuser-Busch`. Note: with this second method, brewery `Anheuser-Busch` is represented in 4 of the top 10 most suspicious (reviewer, brewery) pairs. This brewery might be paying these 4 users.

In [14]:
```
# let's make a (reviewer, brewery) df
reviewer_brewery_df = (
    main_df
    # TODO: check that brewery_name always maps to the same brewery_id
    .groupby(['reviewer','brewery_name'])
    .agg(
        {
            'review_overall':['mean','median','count'], # TODO: can the same user r
eview the same beer twice?
        }
    )
)
# flatten multi-index
reviewer_brewery_df.columns = [
    "_".join(x) for x in reviewer_brewery_df.columns.ravel()
]
# rename
reviewer_brewery_df.rename(
    {
        'review_overall_mean': 'reviewer_avg_score',
        'review_overall_median': 'reviewer_med_score',
        'review_overall_count': 'reviewer_n_reviews',
    },
    axis='columns',
    inplace=True
)
reviewer_brewery_df.sample(5,random_state=123)
```

Out[14]:

		reviewer_avg_score	reviewer_med_score	reviewer_n_reviews
reviewer	**brewery_name**			
Gagnonsux	North Coast Brewing Co.	4.50	4.50	2
pmcadamis	Full Sail Brewery & Tasting Room & Pub	4.50	4.50	1
DiabolikDUB	Unibroue	4.50	4.50	1
todd1	Nøgne Ø - Det Kompromissløse Bryggeri A/S	4.00	4.00	1
Derek	Brauerei Hofstetten Krammer GmbH & Co. KG	3.75	3.75	2

In [15]:

```
# compute avg and median review score for this brewery
brewery_df = (
    main_df
    .groupby('brewery_name')
    .agg(
        {
            'review_overall':['mean','median','count'], # TODO: nunique on beer_id
instead of count
            'bid':['nunique']
        }
    )
)
# flatten multi-index
brewery_df.columns = [
    "_".join(x) for x in brewery_df.columns.ravel()
]
# rename
brewery_df.rename(
    {
        'review_overall_mean': 'brewery_avg_score',
        'review_overall_median': 'brewery_med_score',
        'review_overall_count': 'brewery_n_reviews',
        'bid_nunique': 'brewery_n_beers',
    },
    axis='columns',
    inplace=True
)
brewery_df.sample(5,random_state=123)
```

Out[15]:

brewery_name	brewery_avg_score	brewery_med_score	brewery_n_reviews	brewery_n_beers
Straight To Ale	4.077778	4.0	45	12
Karlsberg Brauerei	3.216981	3.5	53	15
Honest Town Brewery & The Dark Horse Tavern	3.571429	3.5	7	4
Tuscan Brewing	3.388889	3.5	9	2
Traditionsbrauerei Brauberger zu Lübeck	4.500000	4.5	3	1

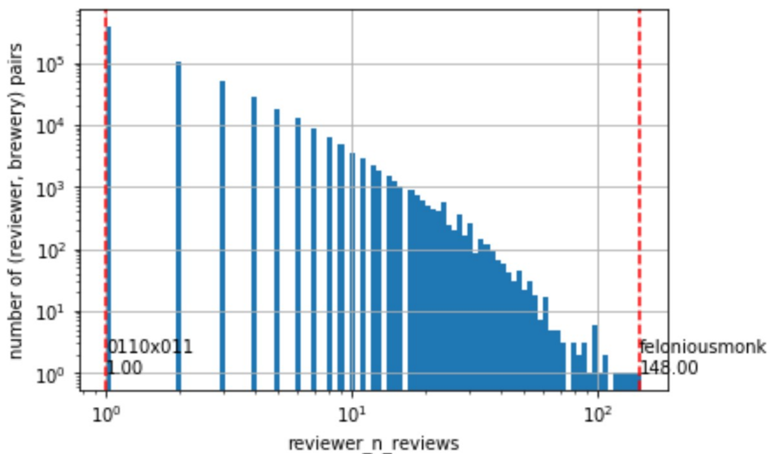
In [16]:
```
enriched_rev_brwry_df = (
    reviewer_brewery_df
    .merge(
        brewery_df,
        how='inner',
        left_index=True,
        right_index=True
    )
    .reset_index()
    .rename({'brewery_name':'brewery'}, axis='columns')
)

enriched_rev_brwry_df.sample(5,random_state=123)
```

Out[16]:

	reviewer	brewery	reviewer_avg_score	reviewer_med_score	reviewer_n_reviews	brewery_av
102543	Gagnonsux	North Coast Brewing Co.	4.50	4.50	2	[illegible]
546740	pmcadamis	Full Sail Brewery & Tasting Room & Pub	4.50	4.50	1	[illegible]
77568	DiabolikDUB	Unibroue	4.50	4.50	1	[illegible]
618358	todd1	Nøgne Ø - Det Kompromissløse Bryggeri A/S	4.00	4.00	1	[illegible]
75971	Derek	Brauerei Hofstetten Krammer GmbH & Co. KG	3.75	3.75	2	[illegible]

In [17]:
```
# EDA: are there reviewers who review the same brewery a lot?
# reuse our good old log-log histogram plotter
plot_hist_and_print_min_max(
    enriched_rev_brwry_df,
    'reviewer_n_reviews',
    'reviewer',
    'number of (reviewer, brewery) pairs',
    loglog=True
)

def display_percentiles_n_reviews_per_pair(df, percentiles):
    """ given non-indexed df with one row per (reviewer, brewery) pair,
    print percentile stats for number of reviews for that pair.
    """
    percentiles = {
        f'{p}%': np.percentile(df['reviewer_n_reviews'], p)
        for p in percentiles
    }
    # TODO: plot cdf instead of printing a dict
    print("percentiles of [number of reviews left by a reviewer on a given brewer
y]:")
    print(percentiles)

display_percentiles_n_reviews_per_pair(enriched_rev_brwry_df, [50,90,95,99])
```

```
percentiles of [number of reviews left by a reviewer on a given brewery]:
{'50%': 1.0, '90%': 5.0, '95%': 7.0, '99%': 16.0}
```



In [18]:
```
# one way to define paid reviewers: they review a lot of beers for that brewery
# note: this does not mean they are dishonest or corrupt
# they could also be die-hard fans, who of course don't need to be paid
enriched_rev_brwry_df.sort_values(by='reviewer_n_reviews', ascending=False).head(5)
```

Out[18]:

	reviewer	brewery	reviewer_avg_score	reviewer_med_score	reviewer_n_reviews	brewery_avg_
401338	feloniousmonk	Minneapolis Town Hall Brewery	4.320946	4.5	148	4.2
36865	Bighuge	Minneapolis Town Hall Brewery	4.518519	4.5	135	4.2
286156	akorsak	Tröegs Brewing Company	3.992481	4.0	133	4.0
115949	Halcyondays	The Bruery	3.968000	4.0	125	3.9
641180	womencantsail	The Bruery	3.756410	4.0	117	3.9

In [19]:

```
# Another way to define paid reviewers:
# They give a score abnormally high to many beers from this brewery,
# They could be robots, or die-hard fans with unusual tastes.
# Parameters to pick:
# i) how many is "many" beers? Arbitrarily going for 16 because 99th percentile.
# ii) what is an "abnormally high" score? Arbitrarily going for .5 point above the
average.

#  add delta of this user's avg score for this brewery vs all users' average score
for this brewery
enriched_rev_brwry_df['delta_avg_score'] = (
    enriched_rev_brwry_df['reviewer_avg_score']
    - enriched_rev_brwry_df['brewery_avg_score']
)

(
    enriched_rev_brwry_df
    .query('(reviewer_n_reviews>=16) & (delta_avg_score>.5)')
    [['reviewer','brewery','reviewer_avg_score','brewery_avg_score','delta_avg_scor
e']]
    # TODO: could also add ['reviewer_n_reviews','brewery_n_beers']
    .sort_values(by='delta_avg_score', ascending=False)
    .head(10)
)
# AH! 4 out of the top 10 pairs come from the same brewery!
# Brewery "Anheuser-Busch" might have paid reviewers.


# TODO: look at the delta for reviewers whose 10+ reviews are all for the same brew
ery
```

Out[19]:

	reviewer	brewery	reviewer_avg_score	brewery_avg_score	delta_avg_score
176699	MrHurmateeowish	Anheuser-Busch	3.820000	2.802286	1.017714
492226	marlinsfan4	Anheuser-Busch	3.785714	2.802286	0.983428
222654	SargeC	Kirin Brewery Company, Limited	3.921053	2.956195	0.964857
505317	mikesgroove	White Birch Brewing	4.583333	3.639617	0.943716
145736	KI9A	Anheuser-Busch	3.729167	2.802286	0.926880
216045	RonaldTheriot	Anheuser-Busch	3.693548	2.802286	0.891262
537188	oteyj	De Struise Brouwers	5.000000	4.128686	0.871314
500136	mempath	Matt Brewing Company	4.357143	3.522816	0.834327
500091	mempath	Boston Beer Company (Samuel Adams)	4.500000	3.692045	0.807955
93040	FARGO619	Stone Brewing Co.	4.789474	4.040428	0.749045

4. Which beer would you recommend given this dataset?

I'm going to re-use results from the previous questions, because I am running out of time.

Recommendations depend heavily on the audience. To make it easier for myself, I'm picking the audience to be: *someone who's never drunk beers before*.

I would recommend them to try the following beers *in this order*:

1. `Crazy Ed's Cave Creek Chili Beer` : low score, yet >100 reviews. Why are so many people drinking it? Is it so bad that it's actually good? Maybe it's a good beer to start with, to anchor expectations.
2. `Citra DIPA` : highest-rated beer with 100+ reviews. Best contrast.
3. `90 Minute IPA` : most reviewed (and therefore probably easy to find), and good score.
4. `Genesee NA` : alcohol-free mouthwash to sober up, if you have to drive back from the pub.

5. Select 4 beers that allow you to “taste the breadth of all beers”

Method:

- Run PCA on beers with 100+ reviews (enough reviews to get signal).
- Then scatter plot these beers along the top 2 PCA dimensions.
- In each of the 4 quadrants, pick the beer with highest L2 norm.
- Bonus: variance explained by the top 2 axes is a measure of "breadth".

Answer:

- `Samuel Adams Triple Bock`
- `Samuel Adams Utopias`
- `Budweiser Select 55`
- `Deviation - Bottleworks 9th Anniversary`
- These beers are 4 extremes spanning (at least) 79% of the variance among all beers with 100+ reviews.

In [20]:
```
def fetch_beer_data(df):
    """
    return df of continuous features and with one column as label,
    and name of label column
    """
    beer_df = build_beer_df(df)
    beer_df = beer_df.query("n_reviews>=100").reset_index(drop=True)
    label_colname = 'name' # label as in text to plot, no to predict
    # keep only continuous features and label
    columns = [
        'abv',
        'n_reviews',
        'review_overall_mean',
        'review_overall_std',
        'review_aroma_mean',
        'review_aroma_std',
        'review_appearance_mean',
        'review_appearance_std',
        'review_palate_mean',
        'review_palate_std',
        'review_taste_mean',
        'review_taste_std',
        label_colname
    ]

    return beer_df[columns], label_colname

beers_df, label_colname = fetch_beer_data(main_df)
beers_df.head()
```

Out[20]:

	abv	n_reviews	review_overall_mean	review_overall_std	review_aroma_mean	review_aroma_std	review_ap
0	4.5	424	3.549528	0.676278	3.205189	0.599741	
1	5.6	877	3.706956	0.629096	3.515964	0.555459	
2	4.2	659	3.266313	0.823304	3.179059	0.706968	
3	4.2	116	3.400862	0.746644	2.853448	0.618614	
4	7.0	716	3.826117	0.566058	3.747207	0.523229	

In [21]:

```
# https://github.com/mGalarnyk/Python_Tutorials/blob/master/Sklearn/PCA/PCA_Data_Vi
sualization_Iris_Dataset_Blog.ipynb
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler

def run_pca(df, label_colname):
    """ Run PCA on a df of continuous features, ignoring colum label_colname
    return a df with columns=[dim1,dim2,dist, label_colname] of the top 2 PCA compo
nents + label
    """
    # normalize
    colnames = [col for col in df.columns if col != label_colname]
    scaled_df = StandardScaler().fit_transform(df[colnames])
    scaled_df = pd.DataFrame(data=scaled_df, columns=colnames)
    # actual PCA
    pca = PCA(n_components=2)
    components = pca.fit_transform(scaled_df) # 2xN df
    explained_variance = pca.explained_variance_ratio_

    # wrangling
    pca_2d_df = pd.concat(
        [
            pd.DataFrame(data=components, columns=['dim1', 'dim2']),
            df[label_colname]
        ],
        axis = 1
    )

    pca_2d_df['dist'] = pca_2d_df['dim1']**2 + pca_2d_df['dim2']**2 # TODO: move th
is in the plotting func instead
    return pca_2d_df, explained_variance

pca_2d_df, explained_variance = run_pca(beers_df, label_colname)
print(f'explained variance: {explained_variance}')
pca_2d_df.head()
```

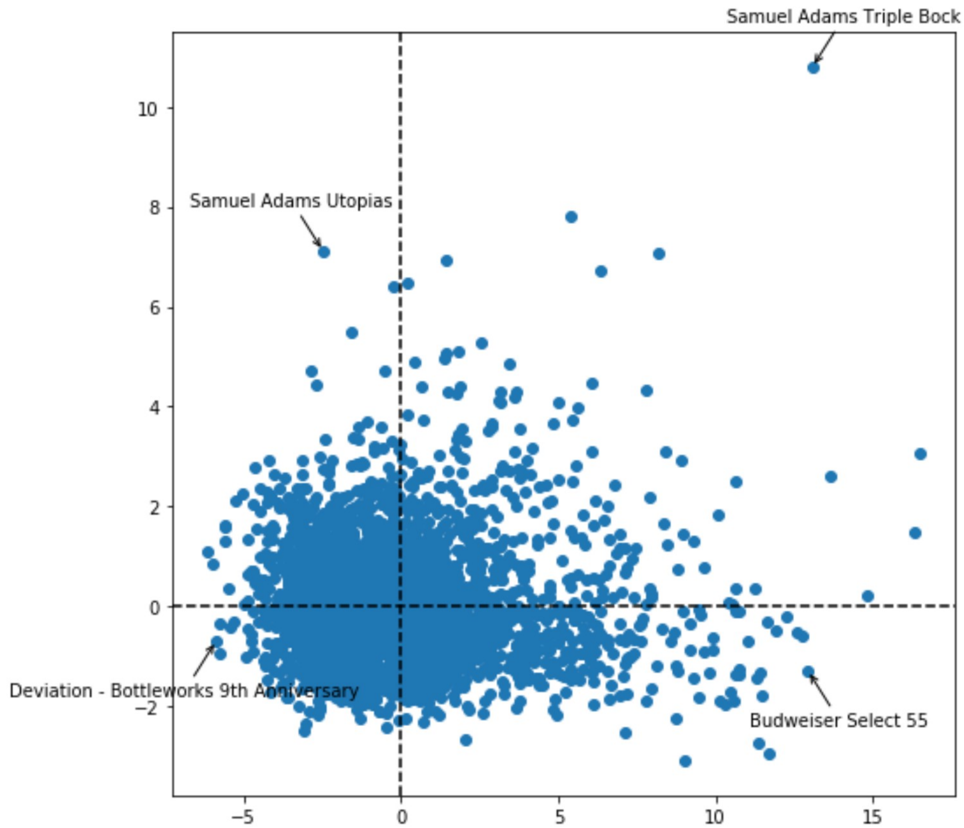
```
explained variance: [0.66718972 0.12332557]
```

Out[21]:

	dim1	dim2	name	dist
0	3.010484	-0.454106	Amber	9.269225
1	0.656231	-0.142338	Turbodog	0.450899
2	5.369391	0.575197	Purple Haze	29.161216
3	4.733301	-1.139280	Golden	23.702102
4	-0.310387	0.217300	Allagash Dubbel Ale	0.143559

In [22]:
```
def plot_pca_2d_point_extremes(pca_df, dim1_colname, dim2_colname, dist_colname, la
bel_colname):
    """ Scatter plot in 2d space,
    point arrows to the 4 corner-most points.
    """
    # https://stackoverflow.com/a/12983510
    fig, ax = plt.subplots(figsize=(8,8))
    ax.scatter(pca_df[[dim1_colname]], pca_df[[dim2_colname]])
    ax.axvline(0, color='k', linestyle='--')
    ax.axhline(0, color='k', linestyle='--')

    # point at most extreme data points in each quadrant
    quadrant_signs = [
        ['>','>'], # top right
        ['>','<'], # bottom right
        ['<','>'], # top left
        ['<','<'], # bottom left
    ]

    extremes = {} # store the farthest (L2 norm) point from origin in each quadrant
    for sign1, sign2 in quadrant_signs:
        query = f'(dim1 {sign1} 0) & (dim2 {sign2} 0)'
        df = pca_df.query(query) # filter data to this quadrant
        name, x, y = df.loc[df[dist_colname].idxmax(),[label_colname, dim1_colname,
dim2_colname]]
        extremes[name] = x,y
        ax.annotate(
            name, xy=(x,y), xytext=(x-1 if x<0 else x+1, y-1 if y<0 else y+1),
            arrowprops=dict(arrowstyle='->'), ha='center', va='center'
        )

    return extremes

extreme_beers = plot_pca_2d_point_extremes(pca_2d_df,'dim1','dim2','dist','name')
print(extreme_beers.keys())
```

```
dict_keys(['Samuel Adams Triple Bock', 'Budweiser Select 55', 'Samuel Adams Utop
ias', 'Deviation - Bottleworks 9th Anniversary'])
```



In [ ]:

In [ ]: